Applications of Dynamic Surface Information for Passive Microwave Precipitation Retrieval

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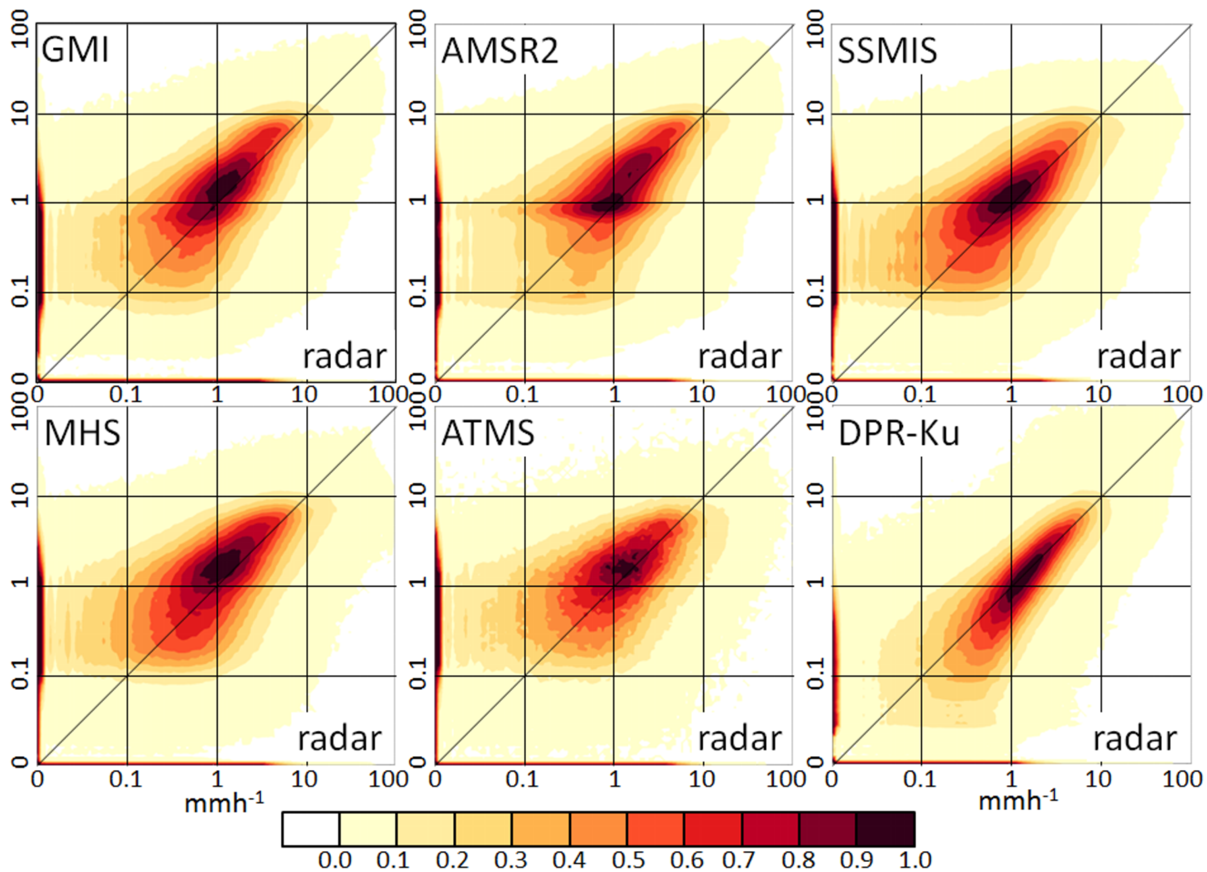
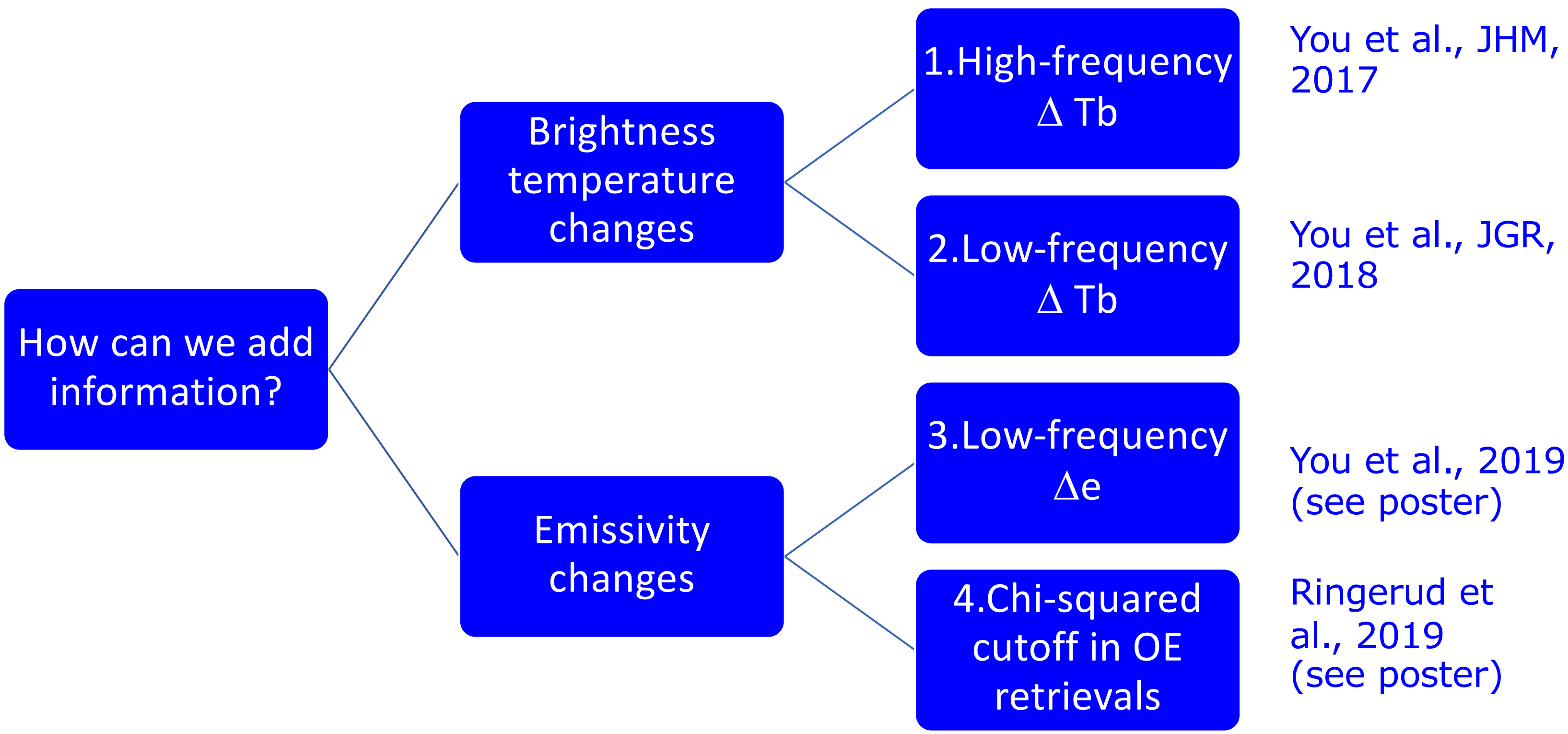
Motivation

The retrieval (in the mean) shows significant overestimation at light rain rates, underestimation at heavy rain rates.



KIDD ET AL. 2017: Normalised density scatterplots of the V05 GPROF and DPR-Ku precipitation products versus surface radar data over the United States region; all products are compared at a nominal resolution of 15x15km (note that zero values are plotted along the x and y axes) - relationship is different over Europe

Approach



How can we add information?
Brightness temperature changes
Emissivity changes
1.High-frequency Δ Tb
2.Low-frequency Δ Tb
3.Low-frequency Δe
4.Chi-squared cutoff in OE retrievals
You et al., JHM, 2017
You et al., JGR, 2018
You et al., 2019 (see poster)
Ringerud et al., 2019 (see poster)

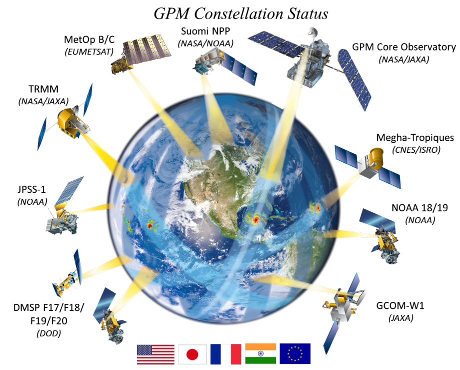
Empirical Approaches: **TB temporal variation (ΔTB)**

$$\Delta TB = TB_{t_P} - TB_{t_C}$$

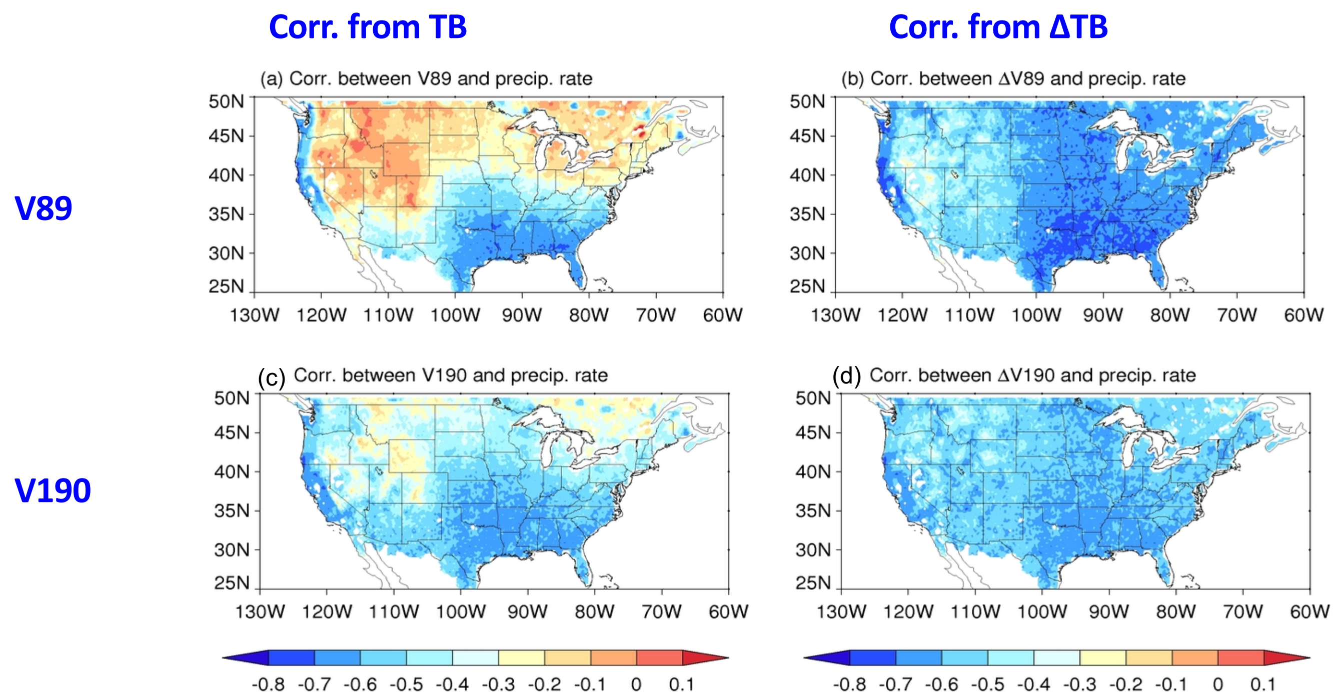
- TB_{t_P} is the current TB associated **with** precipitation.
- TB_{t_C} is the preceding TB at the same location **without** precipitation.
- ΔTB is not the difference between two temporally consecutive TB observations.

$$\Delta t = t_P - t_C$$

- Δt is the time difference between these two observations.
- To mitigate the surface temperature influence, we use the emissivity temporal variation for accumulation retrieval, derived from TB.



Approach 1: Improve cold surface precip. retrieval

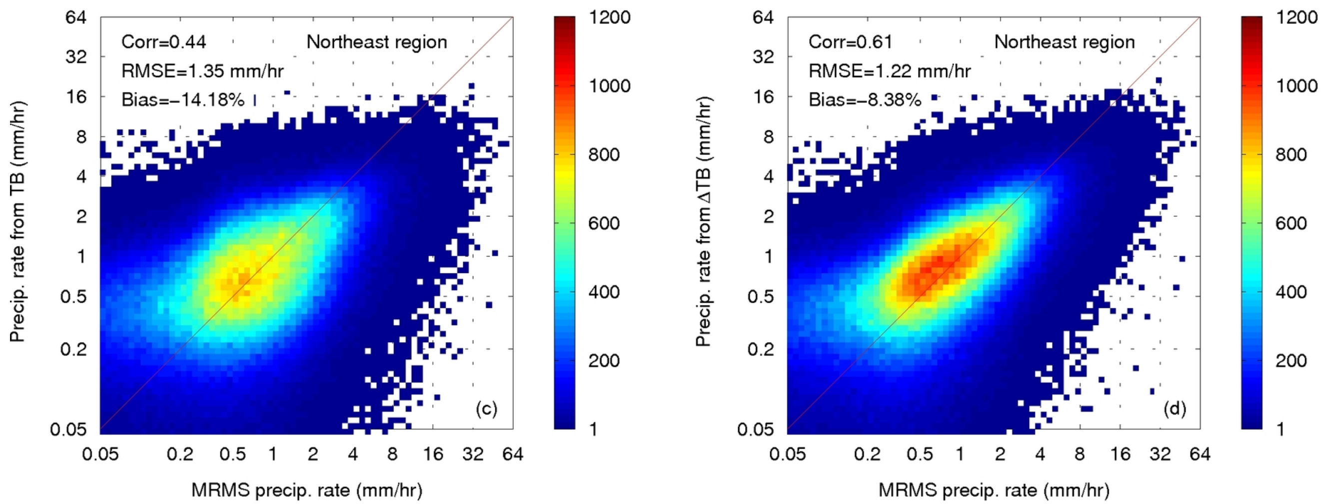


ΔTB correlates more strongly with precipitation rate than TB

You et al., JHM, 2017

Approach 1: Improve cold surface precip. retrieval

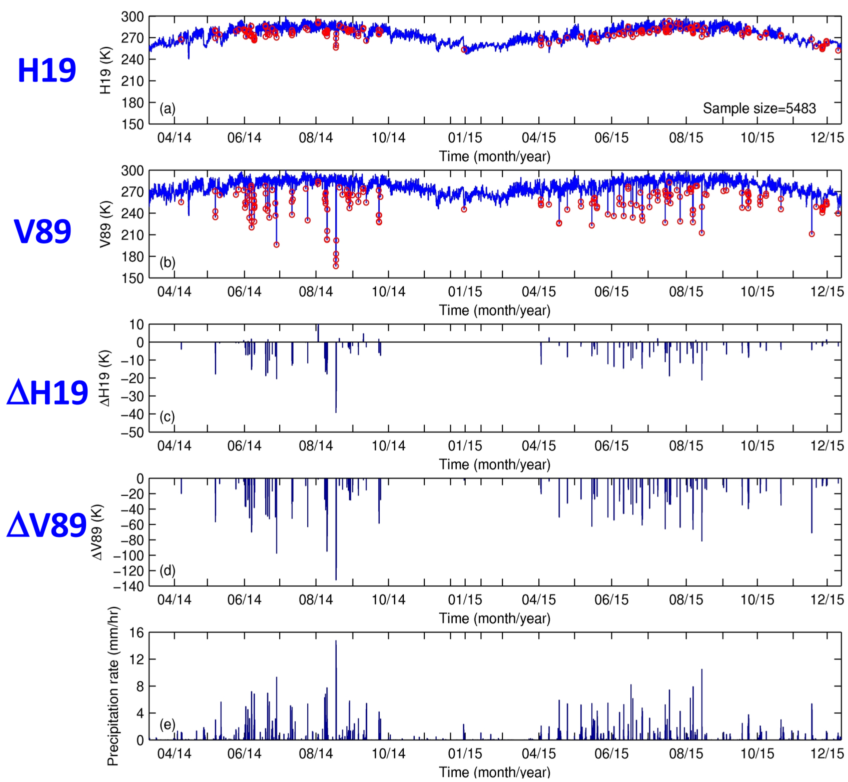
- (V89, H89, V166, H166, V186, V190) vs. (ΔV89, ΔH89, ΔV166, ΔH166, ΔV186, ΔV190)
- **Simple linear regression** (2014-2015 training; 2016 validation).
- Northeast United States (37N-47N, 65W-80W).



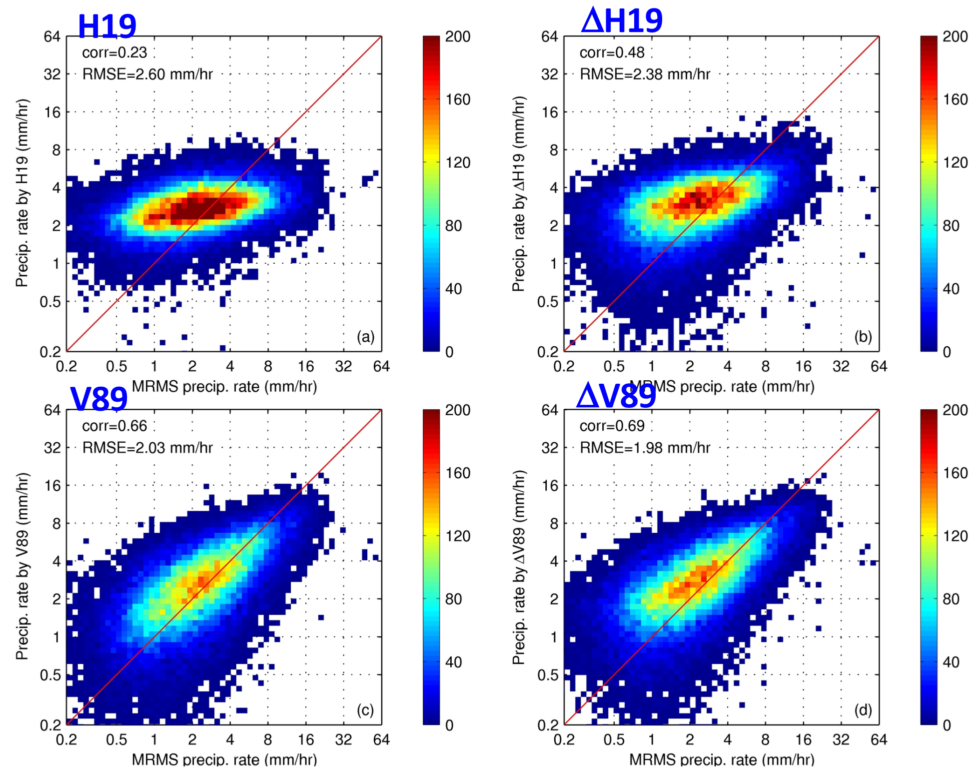
- **Largest improvement is at the lower end of precipitation intensities.**

You et al., JHM, 2017

Approach 2: Low-freq channels for rainfall retrieval



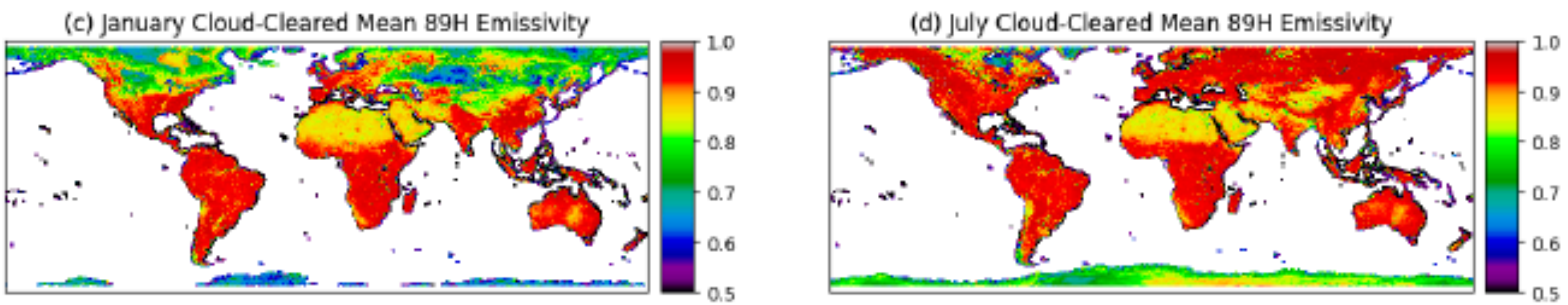
Time series from March 2014 to December 2015 the 0.5° grid box of 101W, 42N for (a) H19, (b) V89, (c) ΔH19, (d) ΔV89, and (e) precipitation rate. The red circles in panels (a) and (b) represent the precipitation observations identified by V19 − V89 greater than 8 K.



You et al., JGR,2018

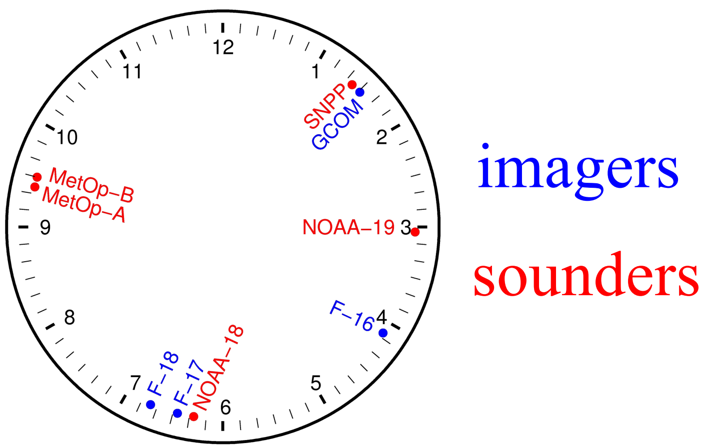
Physical Approaches: Depend on Emissivity Retrieval

- Munchak et al. 2019 (in revision) developed OE retrieval for emissivity, water vapor
- Will be implemented in CMB V7 – take a look at how could enhance passive retrievals



Munchak et al. 2019 (in revision)

Approach 3: Clear-sky TB to retrieve accumulation



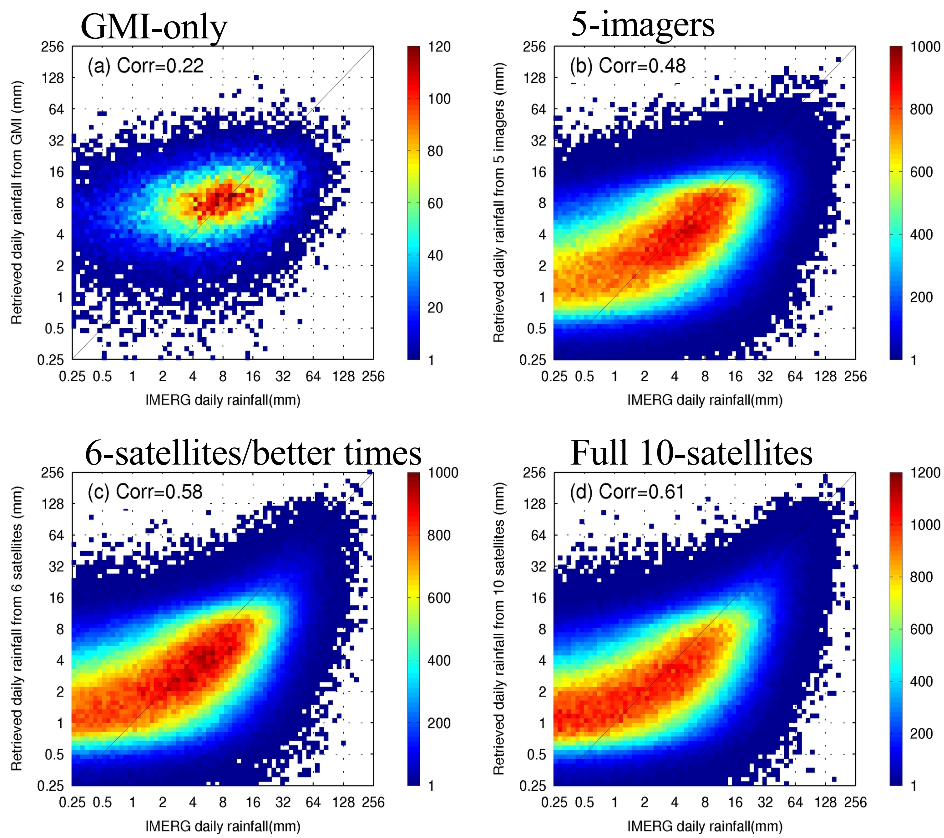
Mean Equatorial crossing time (local time in the morning) for nine sun-synchronous satellites. Satellites with imagers onboard are in blue (i.e., AMSR2 onboard GCOM, SSMIS onboard F16, F17, and F18), and with sounders onboard are in red (i.e., ATMS onboard SNPP, AMSU-A onboard NOAA-18, NOAA-19, MetOp-A, MetOp-B). The GPM satellite has a precessing orbit, which means that it overpasses a certain location at varying times throughout the day.

Based on the Equatorial crossing time, and the radiometer type (imager vs. sounder), we conduct four retrieval experiments with the emissivity temporal variation (Δe) from 19 to 89 GHz derived from different sensors combinations:

- Δe derived from GMI only (**GMI-only**).
- Δe derived from five imagers, including AMSR2, three SSMISs, and GMI (**5-imager**).
- Δe derived from GMI, AMSR2, AMSU-A onboard NOAA19 and MetOp-A, and SSMIS onboard F16 and F17 (**6-satellite with very different crossing time**).
- Δe derived from all 10 satellites (**10-satellite**).

You et al., 2019 (see poster)

Approach 3: Clear-sky TB to retrieve accumulation



Better retrieval performance with multiple satellites:

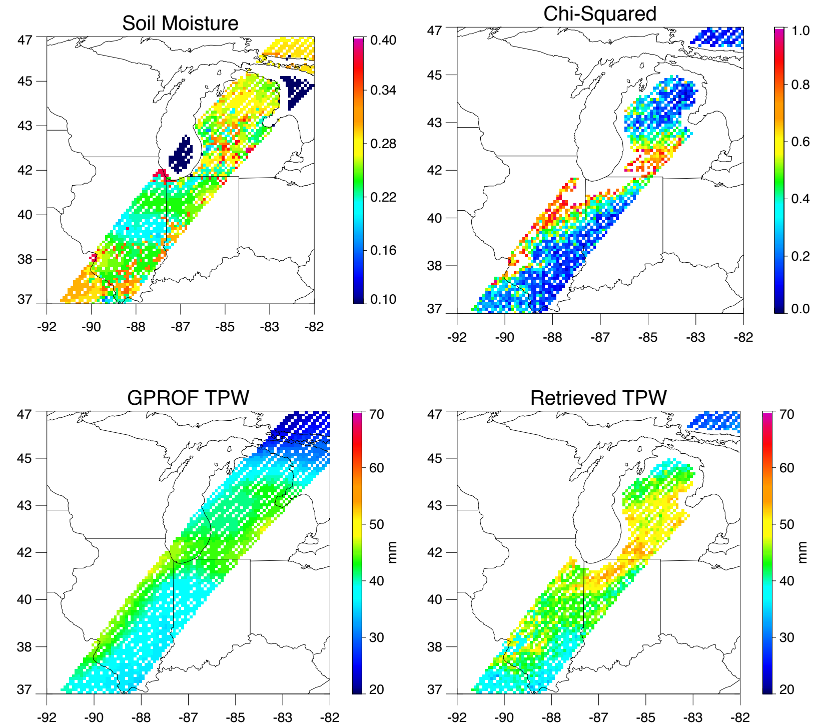
(1)The time difference between the raining day and the non-raining day is shorter with multiple satellites;

(2)The emissivity diurnal cycle is better captured with multiple satellites.

You et al., 2019 (see poster)

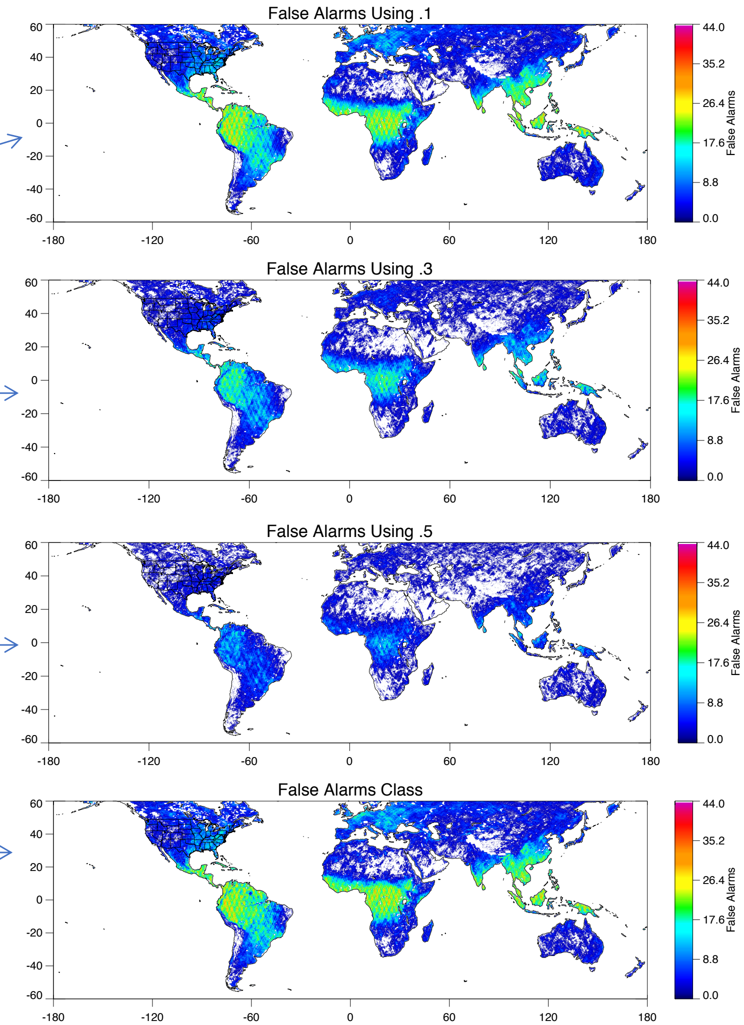
Approach 4: Non-raining OE coupled with Dynamic Constraint Bayesian/GPROF

1. Use Emissivity to Dynamically Identify Snowcover in Retrieval
2. Munchak non-raining OE retrieval is "first pass"
   - Currently set up for GMI, non-snow covered surfaces
   - Normalized error parameter resulting from optimization process is used to identify potential areas of precipitation
   - Retrieved TPW is interpolated across regions above the cutoff
   - Dynamic emissivity is taken from recent non-raining values along with a small range relaxed to account for water on the surface
3. Apply GPROF using dynamic TPW and emissivity
4. Results show promising improvement in GPROF false alarms



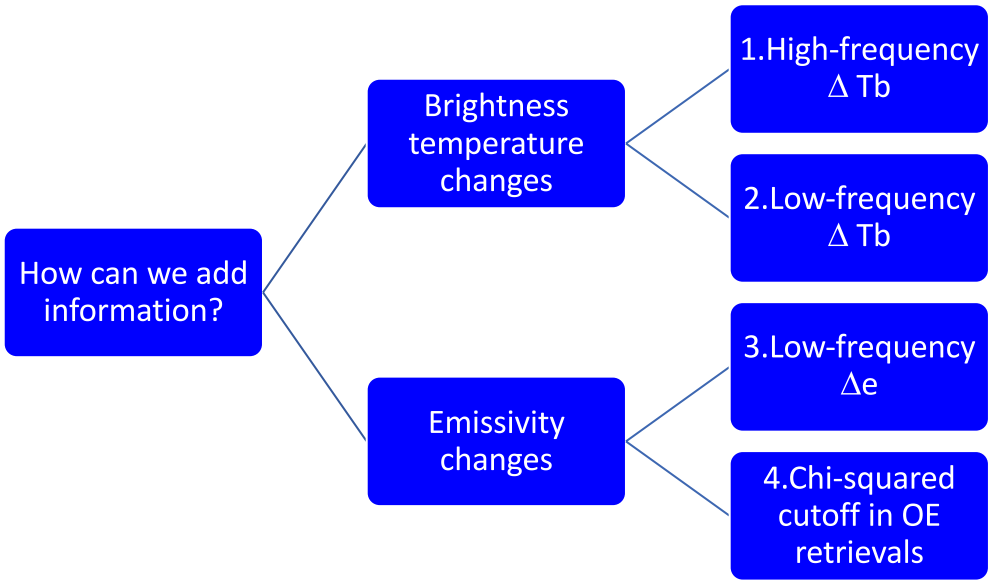
Ringerud et al. 2019 (See poster)

	Correlation	Bias	RMSE	FAR	POD
Chi-sq > .1	0.47	0.044	1.04	0.29	0.91
Chi-sq > .3	0.47	0.038	1.04	0.15	0.84
Chi-sq > .5	0.47	0.035	1.04	0.08	0.75
Class	0.47	0.045	1.07	0.29	0.9



Ringerud et al. 2019 (See poster)

Summary



- **There is information about the land surface "background" in both brightness temperatures and emissivities.**
- **Dynamic emissivity information may be used to reduce false alarms and improve detection of light rain**

Our work also implies that:

- Future satellite missions (either constellation of CubeSats or Geo-Microwave) may further improve ΔTB retrieval performance (ideally same sensors & equally spaced time series).